THESIS

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Development of an Agriculture Technology: A Case Study of Utilizing Digital Imaging and Machine Learning for Identifying Maize Diseases

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Introduction

Smallholder farmers in most developing countries lack of the necessary form expertise that is needed to apply modern agriculture technology and professional advice that will enable them to diagnose diseases and pests affecting plants. This leads to restricted access, especially in rural areas, and substantial crop damage, this consequently has an unfavorable impact on farmers and the general agricultural sector. Moreover, the current scarcity of trained agronomists who are expected to be stationed in rural most is a challenge since they mostly hold a central city region desk job.

These are some of the challenges that made me inclined towards this topic to analyze how this technology area of digital imaging and machine learning can solve such matters. These mobile applications powered by Artificial intelligence have allowed farmers to take photos of their produce, and using an algorithm, determine if the plants are infected by disease or pests at their early stage. Modern farmers require frequent consultations and instant information they can access themselves without leaving their home office or field.

Challenges that small-holding terrace farmers in the developing countries face includes; Limited access to modern terrace farming knowledge, inputs and advisory services. These farmers often use traditional practices since they do not have access to appropriate agronomic advisory services, limited physical access due to geographical barriers, infrastructure constraints and difficulties in accessing/interacting with professional agronomists. (Raizada, 2017)

This research work focuses on the methods of applying digital imaging and machine learning techniques of the application name Agrio for diagnosing the common diseases affecting a major crop in several developing countries: maize. Using this study, it will be possible to assess how effective and accessible AI tools are and whether these tools can assist farmers, especially in developing communities, in making the correct choices regarding agricultural production and development.

Chapter 1

THE PROBLEM AND ITS BACKGROUND

1.1. The Impact of Artificial Intelligence on Transforming Agriculture: Boosting Efficiency and Environmental Responsibility

In terms of the introduction of AI solutions in agriculture, it's the best opportunity to fill in the gaps where professional agricultural consultation is available only via mobile apps. Certain apps will enable farmers to snap pictures of their plants and within seconds artificial intelligence (AI) and algorithms will scan images, flagging any abnormalities on the plants, which can flag diseases. Similar to this, there are also AI tools that come with solutions that feed you details of resource utilization such as the quantity of pesticides used and the amount of water required for irrigation, this will yield better productivity.

In addition, the data from remote sensing devices, including satellite and drone images, can be assessed by AI to gain broader view of crop conditions. All of the aforementioned actions allow the farmers monitor their fields' status not only, but also the risk threats potentially damaging the crop. By utilizing AI solutions, smallholder farmers in developing countries can gain timely and cost effective agricultural information to help in increasing productivity, lowering costs and increasing sustainability. This technology is applicable to solve the problem of insufficient agricultural expertise in this area, as well as to accelerate solving any possible problems in the field and help optimize current farming practices over a large area.

1.2. The Concept and Development of Precision Technologies in Agriculture

Precision farming, or the concept of applying a particular input for the individual plant, originated in the early era of farming. In the pre-industrial age, when most farm businesses were family-owned, farmers could wander around the field and observe the variations in the texture of soil and pattern of crops. However, with the mechanization of agriculture, information related to large-scale operations in terms of management became problematic as opposed to the specificity of details in agronomy.

The commercialization of the Programme and the ability to put precision farming into practice was only made possible with the invention of GPS by the US Department of Defense in the late 197/1980s. It is especially helpful for the identification of a definite area with a certain amount of precision in localization; GPS was essential in the situation of field processing. The initial group of precision farming organizations was formed in 1992, and the first workshop dedicated to precision farming took place in Minneapolis. The first precision agriculture symposiums began in Australia in 1997. The definition and concept of precision agriculture were accepted by the United States Congress in 1997.

The ability to apply precision agriculture resulted from the development of sensors that can be used together with procedures to connect mapped values to farming management procedures. In 1999, GNSS was advanced with further development and higher accuracy which made a major impact on the improvement of operation of precision farming technology mainly in the steep slope region. The first papers providing the overall economic aspects of precision farming as soon as the mid 1990aimed; Lowenberg DeBoer and Boehjle (1996) concluded on the profitability of varying rates of fertilizers. Yield monitoring which is still one of the first ITs in precision agriculture occurred around mid 1995. (Rositsa Petrova Beluhova-Uzunova, 2019).

Precision agriculture can therefore be described as a relatively new management concept that gives an application of technologies and principles related with space and time related to soil and crop production. These technologies include GPS/GNSS, GIS, Virtual reference technique, sensors, Real-Time GPS, Unmanned Aerial Vehicles, and data analysis for improving the precision of inputs and activities. These are; productivity and quantity, improvement of the returns on the inputs that have been used, least interference with the physical environment, and sustainable use of resources. Another benefit of the technology is with the yield and overall profitability because, despite the decrease in inputs, output is higher. Moreover, other benefit includes; reduction in pollution from efficient use of inputs like fertilizers, chemicals therefore it has less effects on the environment.

Precision farming has the following green advantages: because it allows the specific usage of inputs such as fertilizers, pesticides and water, it tends to lower the overall consumption of chemical and minimize the chemical leaching beyond the intended area. This in turns results in reduced pollution of groundwater and the surface water resources. Variable rate technology allows application of nutrients in the right proportions hence reducing instances of nutrient leaching as well as increasing the efficiency of nitrogen utilization. Easy methods of providing water to plants include drip irrigation because they provide the water to the roots at the right time. All in all, each practice in precision farming enhances the utilization of available resources and therefore decreases the emission of the greenhouse gases common among agricultural business. Of the latter, some management practices on a site basis can go a long way in promoting and maintaining the health of the soils to mitigate cases of soil erosion. In a nutshell, the objective of precision farming is to promote unity, efficiency, and useful applications for sustainable agriculture that have limited environmental effects.

It is noticeable that in cases of precision farming, there is a strict adherence to sampling details and sampling at more often intervals. Further, the space and aerial imaging for information gathering also improved bundled with the modern, advanced UAVs. These technologies are also improving in their level of providing such measurements needed for proximal sensing across different sensor types, for fast and nondestructive assessment of the soil properties. Currently, there is an emerging tendency toward real-time management systems based on sensors for variable rate application of inputs such as fertilizers and herbicides. Therefore, the idea of bringing together several data feeds and applying superior levels of analysis is presumably going to improve the decision-making process. Adoption of precision farming practices; prediction of increased gains and positive environmental impacts have become relevant factors. In future advancements there may be an increased emphasis on the precision farming equipment's accuracy, efficiency, and automationt. (Mulla, 2015)

1.3. Factors Influencing Technology Adoption by Smallholder Farmers in Developing Nations.

1.3.1. Technology Factors

Small-scale farmers in developing countries embrace innovative farming practices. technology most often relying on technological characteristics. These are some aspects that have relation to the nature and characteristics of the technology itself which has a strong influence on farmers' decisions whether to purchase the technology or not. Trial ability is a major determinant of adoption to a very large extent because of technological ability. The farmers are more able to accept change when it is a technology they can test at a small scale before having to commit large amounts of resources to introducing it to the market. This allows the farmers to determine, without much loss, all aspects of performance and relevance of the acquired technology. New technology is only adopted moderately to reduce uncertainty and ensure that farmers cover their risks before completely investing in such technologies.

The technological attributes of an agricultural innovation are some of the key success factors for smallholder farmers to adopt an innovation. (Suprehatin, 2021) attributes that affect its adoption include relative advantage, compatibility, complexity, trialability, and observability. In approaching innovation, it is apparent that allowing farmers to choose technologies they consider beneficial is more effective than traditional practices. The marital ones that relate to the anticipation of higher expected revenues, or lower labor requirements, are far-reaching impacts that influence the adoption decisions. In addition, these sentiments are built on experiences, and data gathered from empirical studies, which explore different agricultural technologies' optimization under different conditions.

Technological characteristics are given more importance here, the fact creativity being inventive has the probability to be easily tested will increase their chance of approval. Agriculturalists are increasingly inclined to embrace new technology (Alexander, 2019), which complements the existing resources as well as the manner of operating. Hence, it is crucial to understand these characteristics in endeavoring to find effective strategies for enhancing the uptake of technology by smallholder farmers because these features influence farmers' propensity to change practices within the agricultural chain.

1.3.2. Household-specific factors

The educational background of the farmer often determines adoption as a result of enhancing the capacity to understand, acquire, and act on information relating to new technology. It is also an advantage since older farmers have better potential to give their opinions and efforts to the practice as compared to young farmers who are willing to challenge themselves in finding new methods. The size of households may affect labor availability for new technologies, where many may be able to deploy more labor for labor-intensive technology.

Moreover, the household assets, which are the resources needed to embrace the technologies in agriculture have a positive correlation with the adoption choices. The items that they ranked as productive assets include transportation and other agricultural tools and equipment that enable them to adopt the innovations. Additionally, financial capital is needed; working capital and off-farm income enable farmers to purchase productivity-enhancing inputs hence encouraging adoption. According to research (Mwangi, 2015) smallholder farmers are slow in adopting innovations, particularly where the implementation involves large amounts of capital to be invested. Thus, this interaction of farmer traits underscores the need to use the person-specified approach in order to enhance the use of agricultural technologies among farmers.

1.3.3. Institutional factors

The adoption probability of new technologies in farming is a dependent factor of specific institutional forces. These factors include, in extension service, new technology information, market, and supportive policies. For instance, advanced extension services may provide knowledge and skills needed by farmers so that they can understand and adopt new technologies implying lower risk and more likelihood of success in implementing such improvement. In addition, accurate information assists farmers on the changes warranted by the new technologies, their uses and their impact on the attitudes and the willingness to adopt. Moreover, farmers receiving support from institutions- producer organizations or cooperatives, can assist in obtaining resources, sharing information, and achieving higher leverage in markets that enable farmers to adopt innovations within agriculture more easily. Taken together, these institutional factors can help farmers to adopt new the importance of a conducive support framework to underpin improvements in the agricultural sector.

1.3.4. Economics factors

- **Access to Financing:** The analysis of the financial aspect factors stated that financial capital is central to the adoption of better technologies in agriculture (Yigezu Atnafe Yigezu a, 2018). Credit is the factor that allows farmers to put their capital in inputs and technologies that otherwise would be expensive. Studies have also shown that when farmers have better access to credit, they are willing to adopt innovations because their cash constraints have been eased, and they can undertake other productive activities.
- **Farm Size**: From the above literature, various observations show that farm size is a critical factor in determining the procurement and utilization of technology. Larger farms often

give them more funds, and thus when adopting new technologies do not result in reduced production. Other work also shows an increase in the innovation of technology as larger farms demonstrate the physical space needed to incorporate technology.

- **Market Access:** Market entry is another economic factor that can affect the choice of the technology to adopt. Farming communities are likely to apply new trends in their operations whenever they are sure of a market to sell their produce, as this would enable them to recover their costs. When market competition is realized, the farmers may have no choice but to adopt technologies that enhance production and quality of produce.

Chapter 2

Literature Review

The review of existing literature will be organized into four primary segments, concentrating on the essential technologies that contribute to the creation of the Agrio application.

A. Digital Format
B. Machine Learning
C. Artificial neural network
D. Technology Readiness Level Definition

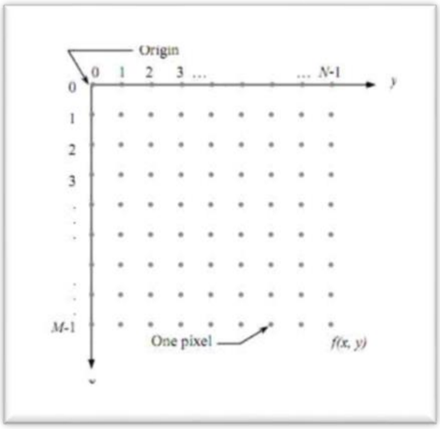
2.1.Digital Image processing

Digital image processing is transforming an image into a digital format, or numerical representation. The objective of image processing can be categorized into two kinds: enhancing the quality of images to enable the human eye to be able to see other details aside from the obvious and allowing the computer to understand what the image is all about (computer interpretation)

2.1.1. Digital Image

A digital image is outlined as an image that may be depicted in terms of a vector or, in other words, a numerical matrix. A digital image can also be described in terms of width and height when plotted on the x and y axes. Any point which is in coordinate from x and y planes is termed as a pixel. Every pixel is an image intensity value of (x,y)or f(x,y). The following example is a point coordinate on a digital image of M rows and n columns with the origin at (x,y)= 0.0.

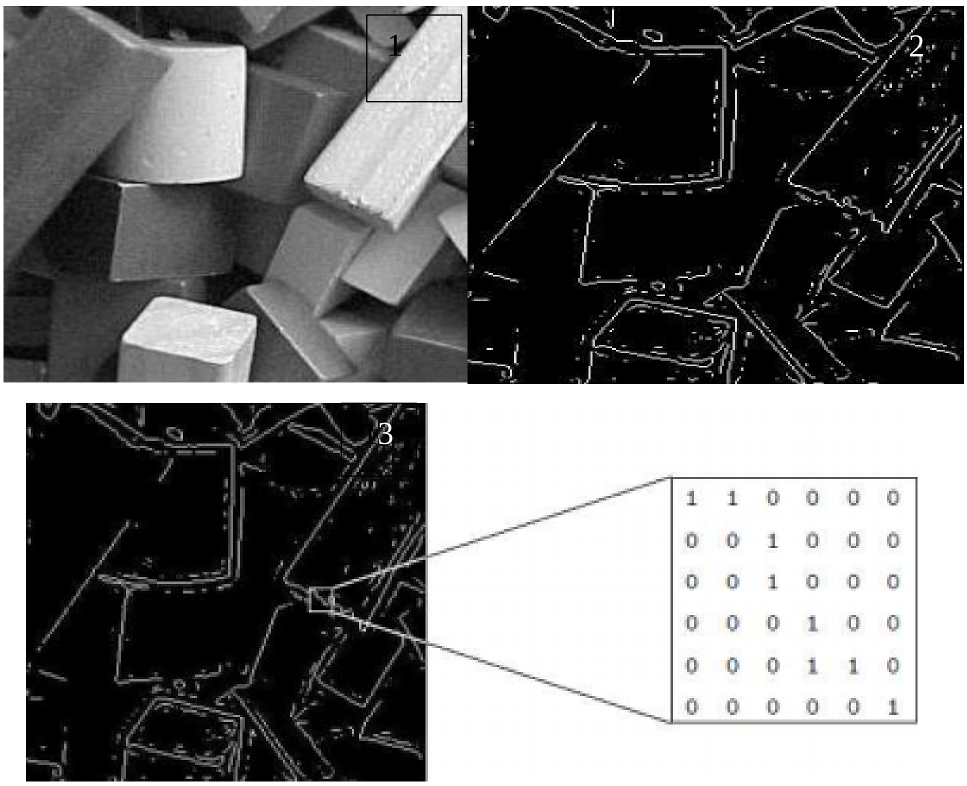
Figure 1: Placement of Co-ordinate Points in the Digital image (Woods, 2002)



A. Digital images can be categorized into 3 distinct types:

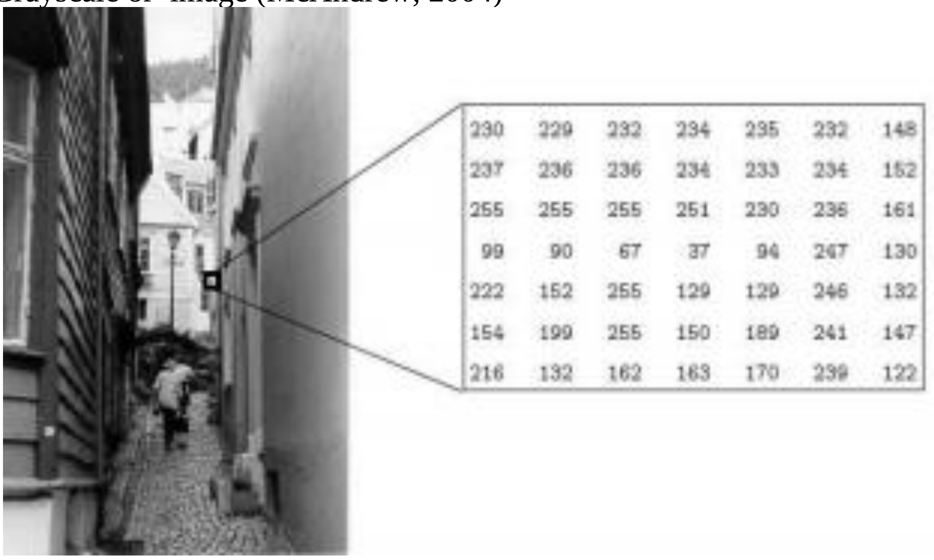
- A binary image (B/W) represents each data point with a single value, using only two colors: White in the case of the value 1 and black in the case of ‘0’ value. Such type of image is usually used where the general analysis of the image is required without going deeper into the texture of the objects and shapes are simply to be identified. Because of the least data complexity and size, binary images are employed in some applications, including edge detection, as shown in Figure 2 below.

Figure 2: Initial image (1), Edge-detected image (2), Binary representation (3) (McAndrew, 2004)



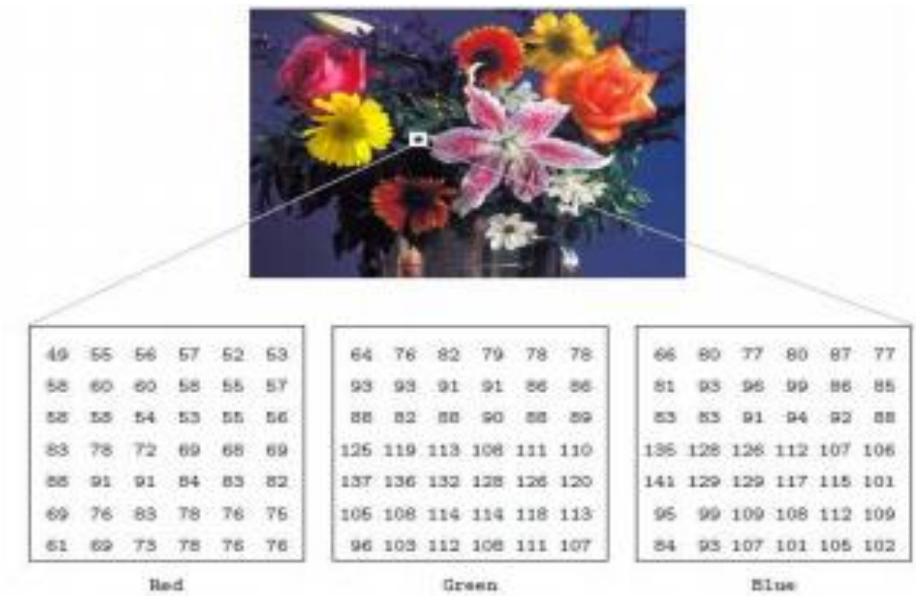
- A grayscale image has an intensity value which shows normal light intensity in shades of gray with each pixel represented by values from 0-black – 255 white, in 8 bits or 1 byte as shown below in the figure.3, as shown in the figure.3

Figure 3: Grayscale or image (McAndrew, 2004)



- RGB color image: a color image composed with three components; Red, Green and Blue which combine to form a three-dimensional vector. It would be possible to set up a light intensity value within just 0 and 255, so up to 256³ (16 777 216) different colour that is why each pixel works 24 bits.

Figure 4: Color or RGB Image (McAndrew, 2004)



- Digital image processing

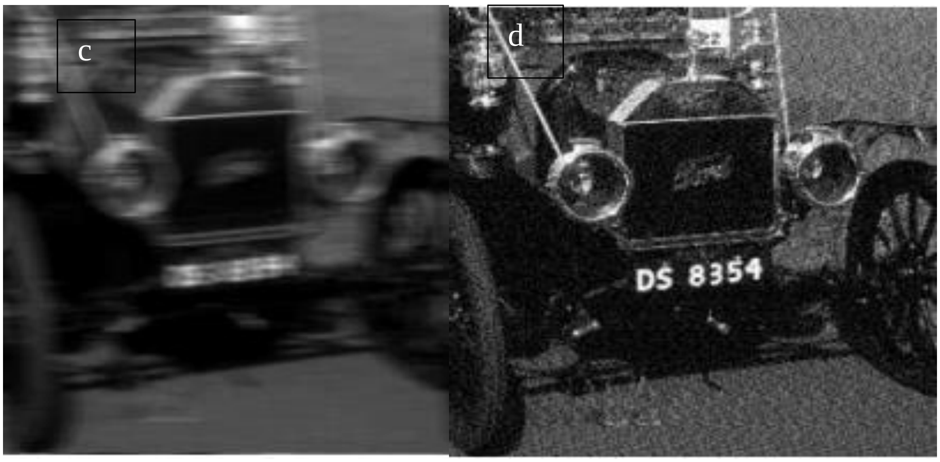
Digital image processing as is indicated above, therefore is the process of altering digital data through various operations on a computer. It might be used to enhance contrast and definition, help to filter out all the miscellaneous noise within the image, or to select certain objects of interest to acquire the best information about the quality and quantity of an image. From the above explanation therefore, it is clear that there exists several phases of digital image processing. Nevertheless, it is necessary to point out that not all tasks are performed for each stage, and it depends on the goals of the analysis. It becomes possible to describe the main stages of computer image processing as follows.:

- The scene restriction is to simplify the intricacies of image processing. Because the processing device's vision and perception are limited and not human-like, it is required to simplify the processing, which includes:
- Object management. In case the object position is not controlled, the processing device has to locate the orientation of the object.
- The ability to focus on an object depends on the distance between the hook or the lens to the object.
- Light management: the important one is light, the production in the perception of the automated system is therefore generated by the light that falls on the object and is reflected by the lens onto the camera sensor. The control of light comprises the identification of lights to be incorporated in the design.For example, in the research done for classifying the quality of the corn tortilla, (Jorge J. Chanona-Pérez b, 2010)fluorescent lamps were used because they emulate the daylight; 18 watts, The most common light source used in food analysis is that of 6500 Kelvin or D65, where it attains a color fidelity of 95 percent. For general quality assessments, the lighting is arranged to be parallel to the camera and is used for illuminating the object under examination; this is called front lighting which only captures the whole object as shown in fig.2 However, some research necessitates the focus on the objects’ distinction in the images, for which using backlighting is made, where the light source is behind the object.

- Image acquisition is defined as the process of taking an image with a camera and then downloading the image’s data into a computer and/or image processing system. This procedure encompasses key components: the camera used in executing the examination on objects is a digital camera which has a light-sensitive item called image sensor, this is a thin strip of several diodes that reacts to the light. Both of these diodes measure the amount or brightness of the light that falls on them, and because they act as individual point-like detectors, they are called pixel image sensors. Standard image sensors are capable of seizing only one level of light density. Normally, these generated values by image sensors are only in a range of 0 to 255 (this range is equivalent to 1 byte or 8 bits, hence resolution of 28 or 256). It is also possible that obtained light intensity values may possess resolutions as high as 16 bits in some cameras. If the value derived is 0 or below it means that the image sensor is in a state where is almost receiving no light or is receiving no light at all and if the value derived is 255 then it means that the image sensor is in a state where it's fully exposed to light intensity.

- Pre-Processing Numerous methods exist for image pre-processing. For instance, noise reduction can be applied to the image depicted in Figure 5 (b), while edge detection can be utilized for Items depicted in the image. presented in Figure 2(2). Furthermore, transformations of images such as rotation, shifting, scaling and edge-detected, and expansion are considered, can be performed, along with color transformations, frequency image analysis, and image compression. (a) Initial image (b) Image following noise reduction techniques Figure 5

Figure 5: Initial Image(a), After eliminating the noise (b), Initial Image (c), After eliminating the blur (d) (McAndrew, 2004)



B. Segmentation

This involves categorizing regions of an image that are homogeneous to have different segments, the main purpose of which is to separate objects from their background. There are two techniques for carrying out this separation process:

- Segmentation based on the distinct threshold values. Threshold values are integer values in the range of [0, 255] and therefore are The strength of the pixel in a grayscale image is comparable. Threshold-based segmentation is performed by transforming the grayscale images into binary images. where pixel value at a specific position is less than or equal to the threshold value then it is set to 0 or made black. That is why if one or several pixels have a value higher than the threshold value they will get a value 255 or will transform to a bright value.
- Edge based on the objects (Edge-based segmentation) starts by the identification of the edge of the object. In digital image analysis, the edge is said to be the point of pixel where the transition from one intensity to the other is greater than a given value. This technique can be described as encircling the object region in the image using edges of the object as exhibited in figure 2(2).

C. Object classification and interpretation

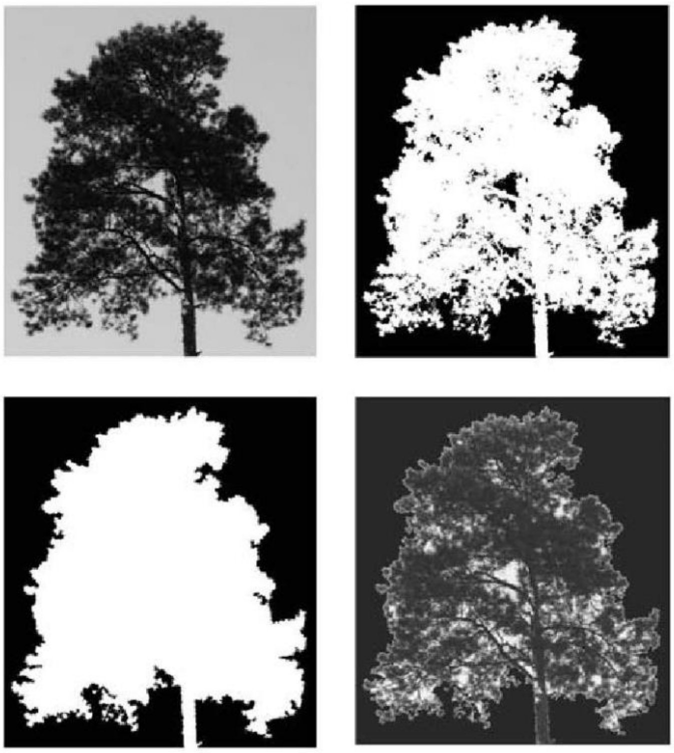
Object classification concerns the sorting of objects based on numbers or mathematical values concerning objects, relative to sample objects of each group. These classifications must however be accompanied by samples from the objects within the classified groups in the system. Concerning size classification, different classification techniques; for example, the k-NN classifier compares the dissimilarity of an object's property vector to the sample group and assigns the object to the nearest group such as using a fuzzy approach with the k-NN to sort apples by their grade. The classification process has also using artificial neural networks (ANN) which work like mini brains for functions like as to inspect defects on surface of apples, bean seeds, the color, the surface characters and the size of to describe saplings etc.

D. Feature extraction

Feature extraction is the process of defining or quantifying numerous attributes of different areas or entities found in an image. For instance, in the pixel method, the area of interest in an image is obtained just from adding up the pixel values; similarly, the length of an object can be obtained by using the perimeter of the object. This process results in feature vector for each object in the image to represent vector of feature values.

Figure 6: Original gray-scale image (a), Segmentation by threshold (b), Isolation of tree crown silhouette (c), Separation of gaps within the crown (d), (Fomin, 2008)

a b



c d

2.2.Machine learning

Machine learning can be described as a branch of AI that concerns itself with feeding algorithms and statistical models to a computer and letting it learn for itself rather than telling it what to look for in a data set. Thus, these systems do not operate as separate programming units that control and make decisions on what to do next but instead analyze data to determine what the result will be, or what decision ought to be made. These advancements are categorized into 3 groups:

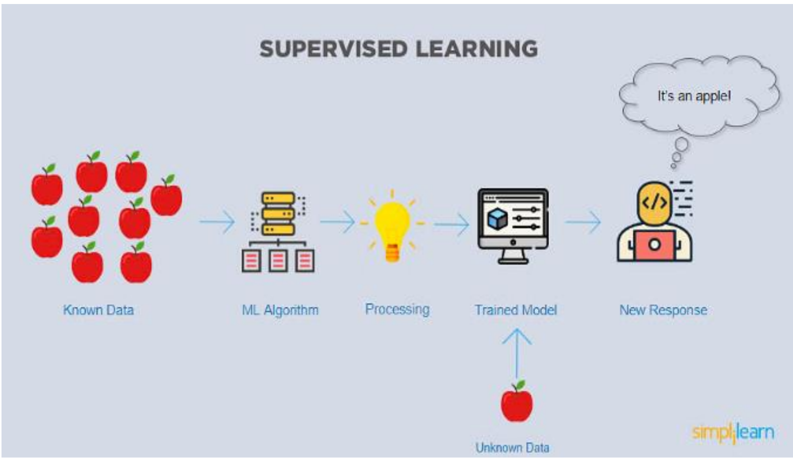
2.2.1 Supervised learning

In supervised learning the data knowledge is attained from the pairs of input and output by the model. The input and output labels are integrated with the input units in a manner consistent with connectionist architecture. This process is designed to help the model learn from the data how to map the input to output so that, in the future when the model receives inputs that are new to the system It is currently situated in a specific position to correctly predict the output that should accompany the input based on its learning.

Each example includes:

- An input (Data feed to the model for example an image, a sentence, or a set of numbers).
- An output is a numerical answer, the answer of a label, for example, whether the image is a cat or a dog.

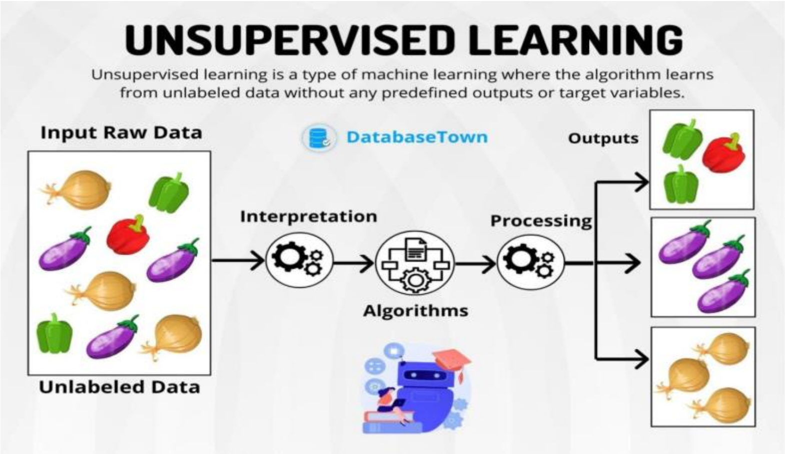
Figure 7 Example of Supervised Learning. (Priyadharshini, 2024)



2.2.2. Unsupervised learning

This is a machine technique of learning where the model finds for itself the input information without having an already labeled input. When confronted with an example, an analytic processor aims to find a definite pattern that has form and shape Or look for instructions in the outcomes. The goal here is to unveil such things as grouping or clustering of data in as much as there is similarity or difference.

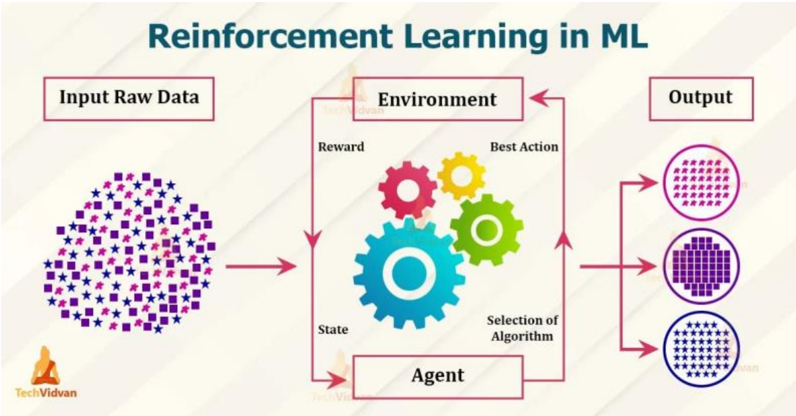
Figure 8 Example of Unsupervised Learning. (Akhtar, 2023)



2.2.3. Reinforcement learning

Like other machine intelligence techniques, reinforcement learning (RL) enables one to learn the best policy without explication. The model or the so-called agent receives feedback from the environment and acts according to the results. As such, the agent is rewarded or punished primarily, depending on the nature of the feedback it garners to determine the right course of action within its model.

Figure 9. Example of Reinforcement learning (Pramanik, 2023)

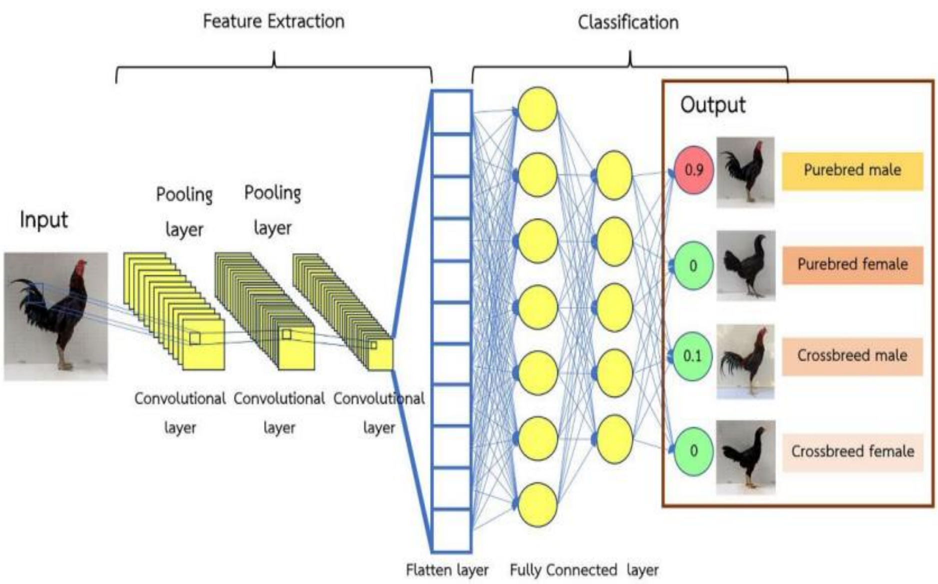


2.3. Artificial neural network

AI is mainly used in agriculture today because it has a sophisticated system that can analyze and categorize different kinds of data with the help of pictures, voices, texts, etc. Thus, the basis of AI is one of its general types, machine learning that learns from the information and then analyzes, predicts, or even performs tasks independently. Machine learning can be performed in several approaches using a software program known as an algorithm. At the time of this writing, one of the most preferred algorithms is the DL algorithm, which employs learning through an ANN model made of several layers like the neuropils of a human brain. LeCun et al in 1998 provided an artificial neural network with convolution and proposed to augment the course of data features by adding more hidden layers and labelled this as Convolutional Neural Network (CNN). It's operating mode feature extraction that starts with determining components within the image that are edges, curves, or slant lines. After that, incorporated into that computation as the input is utilized in the neural network to compute probabilities and facilitate classification, which forms part of the output data. (Surinta, 2019)

The advantage of the CNN structure is that different from conventional machine learning approaches that can only classify and sort data, it can extract images' features and perform classification. CNN framework can consist of convolutional layer, pooling layer or fully connected. The outcomes are illustrated in the neural network as depicted in Figure 10, along with the following details:

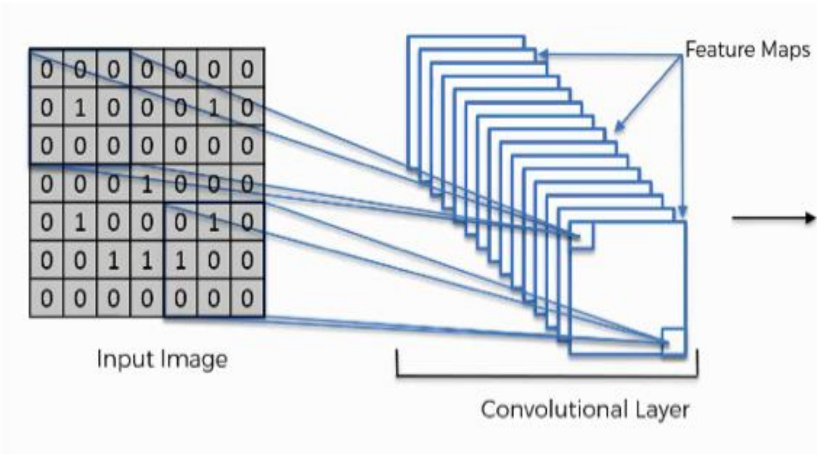
Figure 10 Convolutional Neural Network (CNN) (Sujitra Thipsrirach1, 2023)



2.3.1. Convolutional Layer

The convolution layer is the Fundamental Layer in a CNN and it is tasked with feature extraction no matter the type of input. This extraction takes place by sliding what are called kernels, or a number of filters, regarding the input data. Each filter operates on the input, in other words, it performs matrix multiplication of filter matrix with small portions of the input data called the feature map. In this feature map, some characteristics or attributes of the data have been encoded such as edges, texture or even shape. Other parameters that influence the spatial dimension of the filter when producing the feature map include the stride, a factor that defines the movement of the filter concerning the input, and padding which introduces providing additional width or height to the filter. to cover more regions of input space. A convolution layer may use several filters in order to detect several important features at different levels of abstraction. These extracted features are then passed to subsequent layers to some more processing in attempts to detect other more features on the same input data.

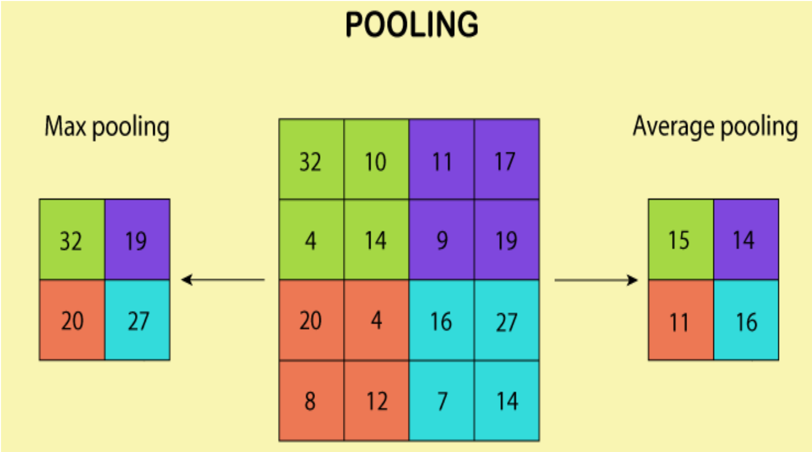
Figure 11 Convolutional Layer (Debasish, 2024)



2.3.2. The Pooling Layer

A pooling layer is one of the components characteristic for Convolutional Neural Networks (CNNs) and used to reduce the spatial size (height and width) of the input data and preserve substantial characteristics. It works by translating a filter over the input feature map and doing an operation which is normally max pooling or averaging on regions in the map. While in max pooling only the maximum value of all the pixels covered in the filter is selected, in average pooling, the average of the pixels is taken. This helps in reducing the number of parameters required and the computations as well as the overfitting problem in exchange for the important features required for classification or recognition tasks..

Figure 12 The illustration of Max pooling and Average pooling (E, 2023)



2.3.3. Fully Connected layer

It is an important layer of a CNN because it makes the final decision after the CNN has learned what constitutes the image. After the edges, shapes and textures of the images are detected in the preceding layers of the programming, the fully connected layer puts together all this evidence to come up with an output of the image. In fully connected layer each neuron is connected to each neuron in the preceding layer, which makes the model look at all the features before reaching an inference. Normally, once the fully connected layer is used, the softmax function is employed, especially in the context of classification problems, the softmax function plays a crucial role. (Debasish, 2024) converts the network's outputs transform into probabilities. for each class, this way the network determines that the input belongs to this certain class (for instance, if the input is an image of a cat, dog, or another object). The network needs to produce accurate results in the final analysis that is based on the learning proce

Chapter 3:

Agrio Application Analysis

3.1.Introduce to Agrio's company

Agrio was launched in 2017 by Sailog LTD under the lead of Nessi Benishti, an Oxford University Alumnus with a first degree in physics. Before he began Agrio, Benishti founded Augmedics, a company that was focused on developing augmented reality for medical applications. Once away from Agrio, he began to investigate the agricultural industry and created an artificial intelligence power app that seeks to revolutionize the way farmers, crop advisers, and gardeners engage with plant health management. For Agrio, AI is a handy, easy, and fast helper for users to help diagnose and treat illnesses of plants. The app is more than a chemical identification; it also offers IPM (integrating pests management) procedures: guidelines to follow, step by step, to control pests or prevent disease. Given that everybody in the agriculture sector from gardening up to large-scale farming will find these guidelines important to reducing insect impacts and boosting yields, Agrio will be of great relevance to whoever has an interest in agriculture.

Its intelligence is based on decades of agricultural experience and it works with agronomists and agricultural experts to enhance the app's AI diagnostic capability. The algorithms learn with every interaction, and Agrio is a forward-thinking Plant Health insights application that provides fresh and sparkling Plant Health referrals each time. Agrio also has a gantry that provides remote monitoring capabilities so the user can see what is happening on plants, and take the appropriate action for correct care and more output on the plants.

Agrio has posted good improvements in the financial performance aspect. According to Tracxn, As of December 31, 2023, the company's revenue stood at $165,000, with a net profit of $54,200. RocketReach. demonstrated that just 6 years later, in 2024, Agrio's revenue hit $6 million in large part to the sharp rise in what's needed for precision agriculture to work. Negro's outing is such growth trajectory that makes Agrio's role in fostering sustainable agriculture through technology efficacious.
With artificial intelligence as part of its unique approach to problem diagnosis, personalized pest management and services, and remote monitoring. Agrio not only looks like it perfects the

digital agricultural sector but also has one of its own. Agrio gives scientists and farmers specs on what they can use their plants on, and then farmers can make the best decision on how to use their plants and what boosts agricultural productivity. The company remains particularly interested in expansion and is still perfecting its platform for use in modern agriculture to solve the problems of continuously changing ecological implications.

3.2.Description of Technology Readiness Levels

Table 1 Technology Readiness Level TRL based Information from Defence Science and Technology Group Australia

TRL 1	Basic research: An investigation starts to look scientific. That tech concept isn't really there yet. Attention is given to new discovery and less so to applications.
TRL 2	Applied Research: It is therefore possible to find practical applications once the basic principles have been realized. Nevertheless, there has been no development of real technology or prototype.
TRL 3	Critical Function or Proof of Concept Confirmed: This culminates at this stage with an initiation of a very active mode of research. Lab experiments may begin, but the apparatus are not ready for any actual implementation.
TRL 4	Technology Validated in Lab: Lab environment is used for testing early stage prototypes. Results demonstrate that projected or modeled systems may be able to meet performance targets.
TRL 5	Laboratory Testing of Integrated: The technology progresses from laboratory trials to being tested for the first time in a simulated or controlled setting, where it will start to encounter real-world challenges.
TRL 6	Technology Demonstrated in a Relevant Environment: Results are demonstrated in conditions that approximate real operational environments. They bridge lab to practical application and bridge the gap
TRL 7	The technology is now nearer to complete implementation at this stage. The prototype system has been evaluated in a practical operational setting.

TRL 8	The system has been fully completed and qualified: Even now it's almost ready for full use, and all tests as well as validations have been already completed. It has proven to be very effective as was the intention with its implementation.
TRL 9	Actual System Demonstrated in Real-World Conditions: This is the phase whereby the technology has already been put in practice and is fully working. That has been confirmed, and it functions effectively in practice..

3.3.Technology Readiness Level of Agrio's AI System

Technology Readiness Levels (TRL) are established measurement tools that categorize the state of development and functionality of the technology, which goes from the conceptual stage to testing and applying it in a real environment. The scale initially presented involves tracing the development of any given system from TRL 1 where more or less the principles of the system along with its potential application are ascertained to the final stage of the holistic real-life testing process of the system at TRL 9.

All of Agrio's developed solutions are based on artificial intelligence and are classified as TRL 9 – all developed solutions are already integrated and effective in experimental systems. Realizing this stage strengthens the reliability and sustainability of the system that Agrio uses for accurate identification of diseases, pest control, and efficient farming. Thanks to this advanced technology, Agrio is also useful for farmers who want to perform an analysis of their crop improvements.

Chapter 4:

Materials

In this subsection, the approach that has been applied to evaluate the Agrio application is explained. The methodology consists of two separate components:

I. The first step of the process is to scroll through the app store and other websites to garner all comments left by users concerning the apps. It will also give information on the emotions and views of consumers who have employed the program under real-life farming conditions.

II. The second part of the study is an experimental initiative. Assessment, in which photographs of real images of affected corn are used to determine the effectiveness of Agrio's AI-based disease diagnostic tool.

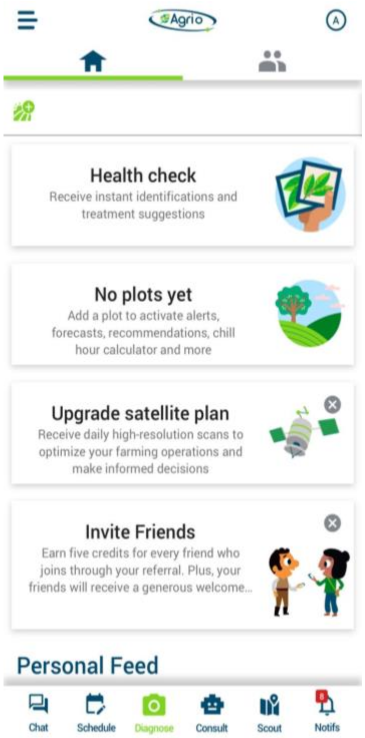
4.1.Showcasing Agrio's Interface

Figure 13 Agrio App Main Screen Layout

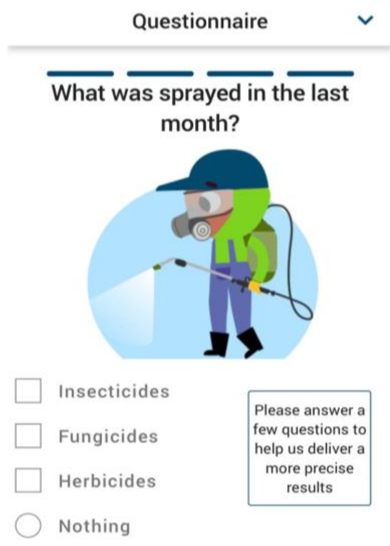
This interface displays the main categories of the Agrio app., including a feature that allows users to perform a straightforward health check using their camera to take pictures of plant parts for quick identification and suggested solutions. With this feature, users can identify issues and receive guidance on appropriate plant administration

Figure 14 Home page Layout (a), Assessment Survey (b), Identification Outcome (c)

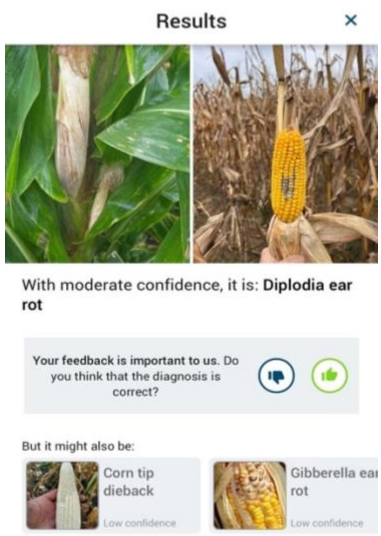
a



b



c



Chapter 5

Methodology

5.1.User Review Analysis:

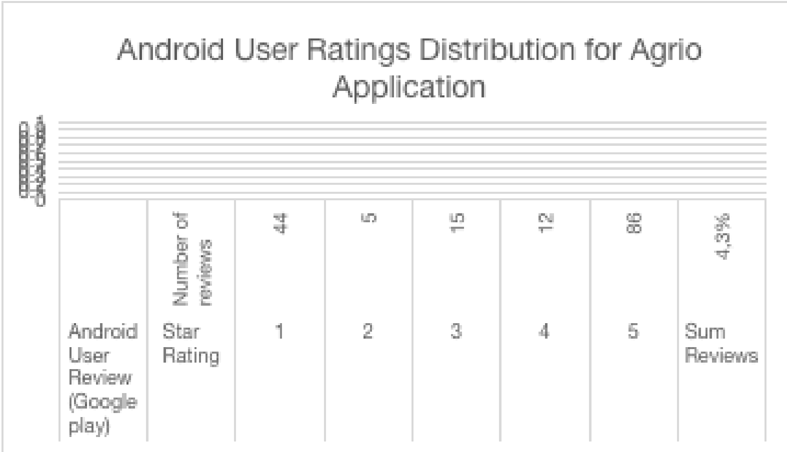
To understand this app better and to get responses from farmers, agricultural professionals, and other relevant users of the Agrio application., feedback was gathered from iOS and Android applications store comment sections, as well as other sites. They assumed the evaluation criterion was to determine the ease of use of the tool and identification of diseases native to plants, as well as, its applicability in controlling pests.

The feedback is separated into two pieces depending on the platform: To minimize the likelihood of developing unique interfaces for the two different operating systems iOS and Android. This section provides a typical finding of a brief review analysis as well as the mean number of stars users have given their products or services. The general objective on the other hand is to gather information from the application and the website and understand exactly how well the application is doing and where it stands to benefit from some modifications. The bar chart below encapsulates user feedback, organized by prevalent themes and ratings from each platform:

- **Android Reviews:** Emphasize the consumers' user responses on the Google Play Store, saying that such features as compatibility with various Android would influence the experiences of users.
- **iOS Reviews:** Pay close attention to performance on the device within the context of the Apple ecosystem and ride the program looking for outstanding features or performance hiccups on iOS.

This comparative analysis gives information about how many interactions with the application are possible, and what areas of the user interface should be dealt with most carefully.

Figure 15 In this bar chart different quantities of a certain grade in the context of the reviews ranging between 1-star and 5-star. This graph shows that we do have users at both ends, at the low end of the satisfaction scale and on the high end of the satisfaction scale which is represented by 1 star and 5 star rating, respectively.



5.2.Overview of Android User Reviews (Google Play Store)

Regarding the Agrio app, 162 consumer reviews that were obtained from the Google Play store were included. These rates came from a diverse population of users and their evaluation pertains to particular aspects of its functionality which is built to diagnose issues in plants, as well as the overall functionality of the program.

- Star Rating Summary

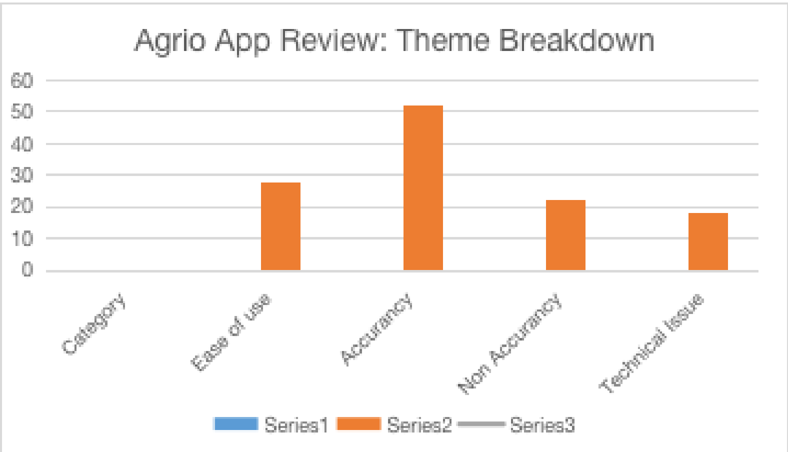
- 27 users bought this app with 44 users (27%) of them stating that they have used it, but they were highly dissatisfied, as they rated it only 1 The main concern of these users could be summarized with the following issues: operational issues with the application, issues in diagnosing diseases, and other system issues.
- A total of 5 users (3%) rated the app with 2 stars and provided negative feedback, though it was not as harsh as the comments from those who gave it a 1-star rating.
- 9% of users, amounting to 15 individuals, rated the app 3 stars, suggesting a neutral opinion. Generally, these users found the app fairly useful but also noted that there is potential for improvement in the future.
- There is Among 86 users, only 12 or 7% of the user rated the app 4, which means that they have relatively high levels of satisfaction.. Some of the users commented that it can be easy to navigate while many others pointed to its efficiency at some point.
- A total of 53 percent of users believe the app is worthy of a 5-star rating, reflecting a strong positive reception from many users. Several users appreciated diagnostic aspects of the app to detect diseases and disorders of plants while it was developed without professionals in mind.

- **Main Topics Recognized from User Feedback:**

In order to gain deeper insights into the user experience, reviews were classified into several main themes:

- It was mentioned 52 times which was the highest in the area of diagnosing disease and pests on plants. Users in general were satisfied with the app's ability to recognize the problems In total, 22 negative keywords reflected the doubts of users about the app's effectiveness because often the application had low results in the identification of diseases in plants. This indicates a two-faced affair where some users have confidence in the app and find it very reliable while others have had their problems solved inaccurately thus reducing their confidence in the application.
- There were 28 reviews about the convenience of the Agrio app where user showed their satisfaction with the design of the app as well as the layout of the app providing easy access to the relevant information.. This was considered good for several reasons by people who have never grown crops and those who have planted crops for several years.
- 18 users complained of technical problems, which included app freezing, slow response of the app, and buggy which impacted its functionality. In fact, majority of these problems were apparent in the 1& 2-star ratings, which showed that there was much room for improvement on the app.

Figure 16 This bar chart illustrates the distribution of user feedback, categorizing both concerns and praises. The primary issues highlighted include inaccuracy and system reliability, along with ease of use.



5.3.Overview of User Feedback from iOS (App Store)

For users on iOS, a total of 153 reviews were gathered from the App Store. The findings highlight elements of the user experience that are favorable, while also noting areas of the website experience that could see improvements.

a) Star Rating Summary:

- 4% of users, totaling 6 individuals, left a one-star review for the app, expressing their dissatisfaction with system errors and inaccuracies.
- 6 users rated the app 2 out of 5 stars, indicating that they are somewhat dissatisfied with its performance and functionality.
- 15 respondents (10%) gave 3 star which indicate that while they did not find this as useful app, they did not completely discount the flaws noted in their use of the app.
- 4 users (26%) said that they will rate the app 4 meaning that they are very satisfied with the app. Most of these users expressed their satisfaction with how easy to use the app is and its reliable operational nature.
- Of the 86 users who completed the survey, 56% of these consumers expressed satisfaction in the app and gave it a perfect score of 5. There were many examples provided, and they noted that it was convenient and easy to use, and the app's capacity to accurately diagnose plant diseases..

Figure 17 The chart shows the quantities of stars awarded, with a focus on the significant share of 4 and 5-star ratings, suggesting that customers are pleased with the application. The instances of 1 and 2 stars were infrequent and tied to isolated incidents of negative experiences.

a) Main Themes Recognized from User Feedback

- Usability: In this case, the respondents preconditioned 14 distinct suggestions for this option, and this was the most often communicated preferred variable. The ease of the interface was perceived and, as such, the perceived ease of use by both the first-time farmers and the experienced farmers, together with those who understood farming but did not use technology.
- Accuracy: Surprisingly, only five users provided their feedback regarding the identification of plant diseases through the app, suggesting that the app met the demands of most of the users. However, a few low-rating reviews could have in some way illustrated cases of wrong diagnoses being made.
- Non-Accuracy: Specifically, 4 out of the 15 users expressed that the app was not very effective at diagnosing diseases. While this number is relatively low, it suggests that some users faced challenges due to the application misidentifying the issues with the plants, leading to concerns regarding its accuracy.
- Technical Problems: in total of 3 users noted problems with the pertinent software, including freezing and sluggishness.

Figure 18 The line chart shows the positive factors discussed regarding ease of use and that negative aspects such as accuracy issue, inaccuracy issue, and technical difficulties mentioned by participants were less frequent. This means that the greatest benefit that users of iOS operating systems expect from the particular application is its easy usage, although there can be certain doubts as to its effectiveness and failure-free performance.

5.4.Evaluation of User Responses from iOS and Android for the Agrio App

Comparing the feedback from the users of both iOS and Android for the Agrio application, it is evident that a user has a different perception of the experience and satisfaction level of an application. Feedback from iOS Users: Nevertheless, it remains surprising that only 5 out of 50 respondents described certain difficulties in the case of the site's accuracy, so the ratings indicate that the majority of users left positive feedback regarding the application. Since the app was granted 86 five-stars and 40 four-stars, one could assume that the majority of users met satisfactory result, such as plant disease identification, which was satisfactory to consumers on the most part. Compared to the positive references, there are four complaints regarding inaccuracy while 28 reviews mentioned the experience, indicating that the app was more often than not accurate with the iOS customers. About technical issues, only 3 has mentioned. which can be compared to the number of Android users' complaints. Coupled with the fact that the majority of the ratings are high, it means that the issues such as the stability in the system, or in its performance, are not a priority concern among users of iOS.

The experience of Android users is more split with 44 one star reviews (27% of all) and 86 five-star reviews (53% in total). A third of the reviewers expressed their discontentment, through 40 users complaining on the aspect of accuracy and 20 reviews contributing to aspects apart from accuracy which shows the users the divide feeling of dependability of the application for plant disease diagnosis. However, there are other criticisms 18 out of the reviews highlighted issues regarding the user interface, for instance, freezing, poor response or slow to load in any action, which has remained a major defect about Ios and Android as well. From these findings, the author was able to find out that using the checked application may cause more frequent and severe issues in terms of technicality on Android than on iOS.

iOS users are usually more satisfied with the app which is seen by higher ratings and few complains regarding accuracy and ills in the system. Although there are some cases of inaccuracy and people complain about it, still one can easily understand the reason; but, looking at the fact that majority of the five-star ratings received reflect that the app has been satisfying most users of iOS. Nonetheless the response from Android users is rather diverse, aside from the expressed dissatisfaction in terms of inaccuracy and unstable functioning of the system. Again, these averages lobster a higher variance than a single rating suggest: such as in the five stars on one side and the one star on the other side meaning that some users had problems.

Chapter 6

Research Results Summary

6.1.Assessment of Agrio App Performance

A study outlines how its research was conducted to determine reliability and efficiency of an application known as Agrio, an AI-based analytics tool. To ensure that the assessments are controlled and clear, we conducted an analytical method using two sources of image data: pictures downloaded from the web (Google images) and actual pictures captured during the internship.

First, the competence of the application in identifying common plant diseases will be tested using images downloaded from various reliable sources on the internet. These images have already been categorized and are widely used in agricultural analysis, where databases has structured for useful for setting up the reference for the app. Thus, we will be able to assess how good or bad Agrio is when the images used in computation have high-resolution images with clear symptoms.

The second group of pictures is derived from the author's own real-world experience during his internship at a company working in maize production. These real-world images show the uncertainties of a field, and this allows us to see how factors such as lighting, image quality, and unclear expressions affect the app's diagnosis. Utilizing both collections of images, the sub-categorization procedure is carried out in this stage based on the accuracy of the diagnosis.

In the final step of comparing agrio's performance on both image sets, a graph and chart will appear in this step to show the App's accuracy rate to give a better overview of how accurate Agrio is.

Table 2 Agrio's application for classifying diseases through Google Images.

Google Image	Agio Diagnosis	Accurate (Yes/No)	Comment
 (Nelson, 2011)	Gibberella Ear Rot	Yes	At the tips of the ear, pink reddish mold will begin and spread downward.
 (Jeschke, 2020)	Moths	No	White grayish mold covered kernels. Additionally, brownish mold begin at the bottom of the ear and then spread upwards.
 (S. Kiritai, 2024)	Common Smut	Yes	Common smut is a fugal disease of the corn ear. Dark, powdery masses form on the cob.
 (Team, 2015)	Penicillium Ear Rot	Yes	Blue mold can be seen on the corn kernel. In addition, the presence of powdery spore masses on the ear may result in surface spotting and the deterioration of the kernels.
 (S. Kiritai, 2024)	Common Smut	Yes	Grayish-blue galls develop on the ear of the corn. Over time, these galls break open, releasing black spores that are a defining symptom of the disease.

 (Robertson, 2019)	Penicillium Ear Rot	No	The typical blue-green mold associated with Penicillium Ear Rot shows no signs of discoloration. The pinkish hue observed in this case is a result of Gibberella Ear Rot from Fusarium species, rather than the blue-green Penicillium. While both molds thrive on regular sugars, Fusarium species generate a pinkish or reddish tint as their mold, in contrast to the blue or green appearance of Penicillium.
 (Jescheke, 2020)	Penicillium Ear Rot	No	Damaged kernels covered white mold, most likely caused by patches of Fusarium proliferatum or Fusarium verticillioides: Fusarium rot in the ears.
 (canada, 2018)	Gibberella Ear Rot	Yes	Beginning at the tip, the reddish-pink mold extends downwar
 (Smith, 2016)	Diplodia Ear Rot	Yes	The kernels have a white mold covering them and are discolored. This fungus disease has the potential to drastically lower crop quality and productivity.
 (Ramay, 2020)	Penicillium Ear Rot	Yes	Growth of green or blue-green mold on the corn plant's ear. The kernels may get discolored and start to smell musty due to the mold.

- Images from practical field

The author took these pictures during a work internship at Limagrain GMBH Porking Station, Germany, trial areas. These fields grew silage and grain maize. Throughout the internship, the following list of common agricultural diseases was also provided: All pictures documented the working environment and any illness symptoms identified while at work. The images has took by iPhone 13 camera with the 12.2 MP (pixels).

Table 3 Classification of Practical Field Image Diseases Using Agrio's Application.

Image from practical field	Agio Diagnosis	Accurate (Yes/No)	Comment
	Diplodia Ear Rot	Yes	The kernel is topped with a white to gray mold, particularly noticeable at the bottom of the ear.
	Unable to classify	No Result	It was not possible for the app function to classify. The Agrio's team Expert is Classify. It is induced by Fusarium verticillioides and is typically seen in hot and arid conditions.

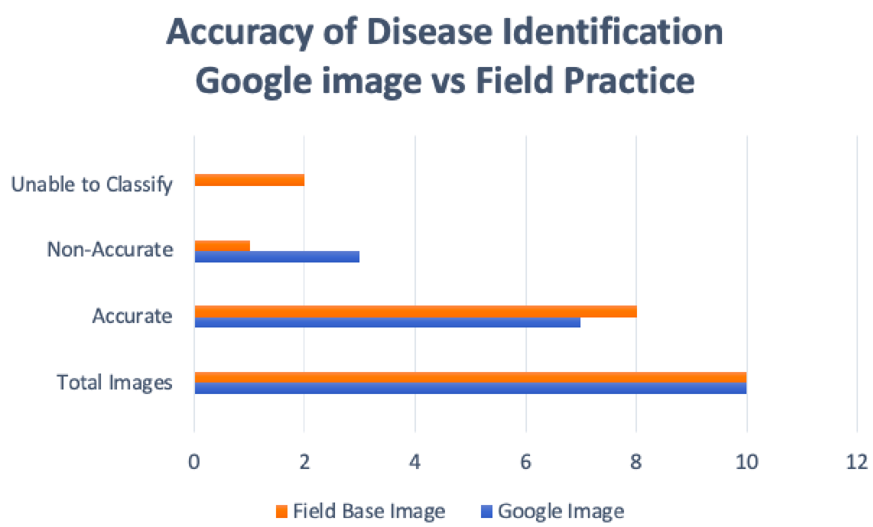
	Common Smut	Yes	Characteristic grayish Galls resulting from smut. forming on swollen galls on corn
	Common smut	Yes	Corn kernels with darkened scars that indicate common smut infection. Characterstic powdery spores already dispersed.
	Aphid	Yes	A sticky substance called honeydew is secreted by corn aphids which build up on the plant. As sooty molds grow on the honeydew, it turns blackish eventually.
	Common Smut	Yes	The common smut form a large black gall on the corn stem.

	Gibberella ear rot	Yes	The white mold begins at the ear tip and appears to spread downward..
	Diplodia ear rot	No	Smut is a very strong indicator of the dark spots on the kernels.
	Diplodia Ear Rot	Yes	A white to gray mold covers the kernels, especially at the bottom of the ear.
	Unable to classify	No Result	Incapable of Categorize by the AI. Although, the Agio team's knowledgeable staff have categorized the birds-damages.

6.2.Research Results Summary

A comparison of the recognition accuracy in relation to Google images and field images demonstrated the effect that the quality of the image has on Agrio's AI diagnostic performance. The findings showed that accuracy was higher with field-sourced images since the pictures were clearer, contained more details, and were brighter for the AI to classify. In this research, a majority of the field images received accurate classifications, highlighting the significance of having high-quality image input for attaining dependable outcomes in the identification of diseases through AI technology.

Figure 21. Evaluation of the precision in disease detection comparing Google images and images captured in the field.



Nevertheless, it was somewhat unexpected that despite having higher-resolution images from the field, the AI failed to correctly classify twice. Cases like this highlight one of the main drawbacks of machine learning models, which seems to be that certain indications of disease can be too subtle or subtle for the AI to identify without additional training. In these cases that have not been identified, agrio's enhanced functionality is used, where users can access expert opinions. Using this feature, the Agrio team will be the ones to correctly identify the images, proving that sometimes human intervention is a complement to AI.

On the other hand, images coming from Google are characterized by lower disease classification accuracy and a larger percentage of unclassified diseases. This distinction can be explained by the fact that images coming from Google or from the Internet can have several poor quality features, some of which may be blurry, have poor quality, and experience varying lighting situations, which influences the AI's ability to identify disease traits.

This comparison makes us realize the image quality problem in AI diagnosis in the context of agricultural practices because many images used in the field or real images, AI can see and capture the quality better because they are clearer, but sometimes it cannot identify because some images may be more complex, making AI unable to check. Therefore, human assistance is important in some cases to make the image classification correct.

Apart from the diagnosis, the functions of the Agrio application also include an opportunity to consult with agronomists regarding various problems of plant health. This, a feature that the author of this study exploited, not only allows farmers to get help with the identification of disease but also address other general issues affecting farming. Because agronomists can detail how to solve particular issues and recommend appropriate techniques, it is a handy tool for small farmers who might not regularly consult with an agricultural professional as a result of isolation. This function remarkably minimizes the guesswork for farmers, specifically on what may be causing the problem with crops and how the problem can be solved. While it may take a while to wait for the answers, the knowledge shared by experts can change the productivity of farms and the health of the crops.

Furthermore, it is also important to note that Agrio can be accessed in over 15 languages hence it is one of the most adopted tools by farmers across the globe. This way, the app guarantees that farmers of different nationality and geographical location will be able to comprehend and apply suggestions of experienced colleagues without significant language interference.

Chapter 7
Conclusion and recommendation

7.1.Conclusion

This research has shown that digital imaging and ML can be used effectively in agriculture, especially to diagnose diseases in maize. This means that the use of AI solutions like the Agrio application is a big leap forward in quickly and efficiently diagnosing diseases that affect smallholder farmer. As it can be observed from both Android and iOS feedback, the Agrio app has been useful in assisting in diagnosing diseases; however, even with its effectiveness, strengths and weaknesses include the following: technical functionality and accuracy across varied environmental conditions. The performance assessment of Agrio by the study on (Google images) and real-life (field images) images reiterates the impact of image quality on AI diagnostics. While field images were more realistic, reflecting real conditions, some issues with AI in identifying more sophisticated and/or nuanced stages of the disease in question were observed as well. These findings demonstrate that even when the machine learning technology could enhance the efficiency and minimize dependency on professional's opinion, the humans remain irreplaceable in some cases.

Furthermore, Agrio has the great function of linking between the agronomists and the farmers. This application makes farmers able to consult directly with agronomic experts and gain real-time assistance. Through this capability, the gap between specialist knowledge and practical implementation is minimized bearing the necessary information on crops and pests to the farmers.

In summary, although Agrio and other related AI applications are immense potential, the further advancements is still required to improve diagnostic accuracy and flexibility concerning various disorders. This is something that must continue to evolve as AI is expected to further transform agriculture toward sustainability with farming people across the globe. The inclusion of an expert consultation system within the body of the application not only brings an advisory role into the advancements of the farmer and agronomist but also strengthens the crop health and yield production.

7.2.Recommendation

However, even with all the developments made to the applied machine learning system of the Agrio app, the need to improve the precision of the system cannot be overemphasized. The first direction is the further development of AI for detection of diseases, in particular with the help of improving the model based on the use of more sophisticated and diverse data on plant diseases. This approach will allow the AI to fit more conditions and give more accurate identification in different lightings or blurriness of images.

New disease or pest emergence, changes in climate, or in the ways recommendations are used by the farmers are compensated by regular updates and continuous training of the AI model. This makes it dynamic in that it is created with the possibility of continuously incorporating solutions to the emerging issues in these agriculture in the future. As the model is constantly improved using the updated data, Agrio is able to assist users more effectively providing the correct diagnoses of problems and recommendations in an environment that is constantly shifting.

Besides these enhancements, the Agrio platform has an option that permits users to seek advice from seasoned agronomists. By this function, a farmer is able to contact a fellow agronomist to seek clarification on any plants' issues, diseases that may be affecting them or any advice one may need on the field. This connection is thus useful and acts as a medium that brings together farmers and other professionals. By creating that bridge between the practitioners as well as specialist, Agrio tends to establish a system uphold that continuously offers support so as to improve the flow or productivity on the real time basis. Even though this feature is only available to the paid membership, the price of the basic package is still reasonable for many users to afford hence making consultation from experts worth the dime to improve the productivity of the farm.

To overcome current limitations, Agrio could further develop this expert consulting service by attending to response time AND possibly adding more superior image processing algorithms to increase the AI performance with low-quality images. The additional features would enhance the app's functionality in helping the farmers besides providing them with a strong tool in the form of AI supported recommendation engine that would minimize the dependence on experts in emergencies or allow for faster identification and treatment of diseases.

To summarise, Agrio can help specialists in farming reduce their workload while still giving the farmers dependable tools. These recommendations will allow the application to be an even more valuable tool in precision agriculture and to further enhance productivity and practices of sustainable agriculture in daily practice.

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